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ECG Signal Pre-processing by Lifting Scheme Constructing Multi-resolution Morphological Decomposition

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Abstract: The target for Electrocardiogram (ECG) signal pre-procession was baseline correction and noise suppression with as low as possible waveform distortion. Morphological operations based pre-processing methods had superiority on reducing waveform distortion and computing complexity. However, linear structure element would cause block effect which was the reason for waveform distortion. Therefore, a novel pre-processing method based on lifting scheme constructing multi-resolution morphological decomposition was proposed in this study. The algorithm adopted cubic spline interpolation for design of predicting and updating operators to effectively reduce the block effect. By simulation to standard test ECG signals and comparison with other pre-processing algorithms based on wavelet transform and multi-resolution morphological decomposition, it was concluded that this algorithm could achieve good performance in mean absolute differences, max difference and root mean square error. The waveform distortion was visually acceptable and the computing complexity was not high.

Key words: Baseline correction, multi-resolution decomposition, lifting scheme, morphological operation

INTRODUCTION

ECG pre-procession consisted of baseline correction and high-frequency noise suppression. It was the first step in ECG processing and the foundation for the following operations such as characteristic waveforms detection (Hendel *et al*., 2010; El-Asir and Mamlook, 2002) signal compression and so on. Nowadays, ECG pre-processing methods based on Wavelet Transform had been acknowledged for its good performance in separating frequency components and de-noising them properly (Lu and Zhang, 2000; Fu *et al*., 2004). Wavelet db4, whose morphology was similar to basic QRS complex, was usually adopted as the mother wavelet for transformation (Chowdhury and Chakrabarti, 2010). To clearly separate baseline and high frequency noise from ECG signals, high level decomposition was needed. However, this would lead to heavy computational burden and waveform distortion would not be avoided. Mathematical Morphology (MM) had been extensively applied in signal and image processing field because of its robustness and self-adaptability in extracting morphological information. Furthermore, algorithms based on MM could be easily accomplished by simple set operations. Baseline correction and noise suppression were achieved by changing local characteristics of ECG signals (Sahambi *et al*., 1997; Sun *et al*., 2003; Zhang and Zhao, 2002). But shape selection of Structure Element (SE) had an effect on pre-processing performances. Linear SE could cause block effect and waveform distortion became more serious with longer SE.

ECG pre-processing methods based on multi-resolution morphological decomposition had been proposed to improve performance of noise suppression (Tianyao *et al*., 2007), yet the block effect was still the main reason for waveform distortion. Therefore, in this study, a novel ECG pre-processing method was proposed to improve the performances in both noise suppression and block effect. Lifting scheme was employed to construct multi-resolution morphological decomposition and cubic spline interpretation based updating operator was developed to eliminate block effect. As a result, waveform distortion was smaller than other method based on morphological operations.

MATERIALS AND METHODS

Multi-resolution morphological decomposition: Traditional multi-resolution decomposition focused on linear multi-resolution pyramids which filtered signals by linear operations, such as Fourier and Wavelet Transformations. Although these schemes had developed

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various mother functions for different applications, scaling a signal or image by linear operators might not be compatible with their inherent characteristics (Goutsias and Heijmans, 2000). A number of nonlinear multi-resolution decomposition methods were presented as image processing and analysis tools (Swarnalatha and Prasad, 2010). Among them, methods based on morphological operations had superiority in reserving signal morphology during procession which was an important criterion for evaluating ECG pre-processing algorithms.

Multi-resolution morphological decomposition (MMD) removed specific components in signals by morphological filter as approximation signal and residue as detail signal respectively. By repeating this procedure, the original signal was decomposed at different levels and approximation signal at lower level can be reconstructed by approximation and detail signal at higher level.

Let $j \in J \subseteq Z$ be the level index in multi-resolution decomposition, signal domain V_j and detail domain W_j at level j. Under this framework, define signal analysis operator $\psi_j^{\uparrow}: V_j \rightarrow V_{j+1}$, detail analysis operator $\omega_j^{\uparrow}: V_j \rightarrow W_{j+1}$, synthesis operator $\Psi_j^{\downarrow}: V_{j+1}+W_{j+1} \rightarrow V_j$, or signal synthesis operator $\psi_j^{\downarrow}: V_{j+1} \rightarrow V_j$ and detail synthesis operator $\omega_j^{\downarrow}: W_{j+1} \rightarrow V_j$, respectively. According to pyramid condition, if $\psi_j^{\downarrow}\psi_j^{\uparrow} = id$ on V_{j+1}, the original signal could be perfectly reconstructed by $x_j = \psi_j^{\downarrow}(x_{j+1})$ and id denoted the identity operator.

Define set L is a complete lattice if every subset K of L had a supremum $\vee K$ and infimum $\wedge K$. For two complete lattice L and M, let ε: L→M and δ: M→L be two operators, we said (ε,δ) constitutes an adjunction between L and M if:

$$\delta(y) \le x \Leftrightarrow y \le \varepsilon(x),\ x \in L,\ y \in M \tag{1}$$

And ε was called an erosion and δ was called a dilation. For any $\{x_i|i \in I\} \subseteq L$ and $\{y_i|i \in I\} \subseteq M$, they had the following property:

$$\varepsilon\left(\underset{i \in I}{\wedge} x_i\right) = \underset{i \in I}{\wedge} \varepsilon(x_i) \tag{2}$$

$$\delta\left(\underset{i \in I}{\vee} y_i\right) = \underset{i \in I}{\vee} \delta(y_i) \tag{3}$$

Therefore, $\varepsilon\delta \ge id$ became a *closing* on M and $\delta\varepsilon \le id$ became an opening on L.

When:

$$\psi_j^{\downarrow}\psi_j^{\uparrow}\psi_j^{\downarrow}\psi_j^{\uparrow} = \psi_j^{\downarrow}\psi_j^{\uparrow} \ne id$$

$$\hat{x}_j = \psi_j^{\downarrow}(x_{j+1}) = \psi_j^{\downarrow}\psi_j^{\uparrow}(x_j)$$

represented the approximation of $x_j, \psi_j^{\downarrow}\psi_j^{\uparrow} \le id$ was an opening and $\psi_j^{\downarrow}\psi_j^{\uparrow} \ge id$ was a closing. It was concluded that $\psi_j^{\downarrow}\psi_j^{\uparrow}$ was a morphological filter at level j and multi-resolution decomposition could be constructed by $\{\psi_j^{\downarrow}\psi_j^{\uparrow}, j \in J \subseteq \mathbb{Z}\}$. As a result, ECG signals could be decomposed by multi-resolution morphological operations and signal at level j was an approximation of the original signals.

Lifting scheme constructing MMD (LMMD) ECG pre-processing algorithm: Define ECG signal as f(n), n = 0,1,2,..., N-1, symmetrical SE as B(m), m = 0,1,2,3..., M-1, erosion and dilation of ECG signal could be denoted as following:

$$(f\Theta B)(n) = \min\ \{f(n+m)-B(m)\}\ m \in 0,1,..., m-1 \tag{4}$$

$$(f \oplus B)(n) = \max\ \{f(n+m)-B(m)\}\ m \in 0,1,..., m-1 \tag{5}$$

Opening operator was $f \circ B = (f\Theta B) \oplus B$ while closing operator was $f \bullet B = (f \oplus B)\Theta B$.

LMMD ECG pre-processing algorithm could be divided into two parts: baseline correction and noise suppression. Baseline correction was conducted by the following morphological filter (Chu and Delp, 1989):

$$f_b = f_o \circ B_o \bullet B_c \tag{6}$$

where, f_o was the original ECG signal, f_b was the detected baseline wandering, B_o and B_c were two linear SEs which depended on the duration of characteristic waveforms in ECG signals T_w and sampling rate F_s. Commonly, T_w<0.2 sec, therefore, let B_o = 0.2 F_s and B_c = 1.5 F and B_o = 0.3 F_s.

According to MMD method, ECG signals after baseline correction could be decomposed at level j as following:

$$x_0 = F_o - f_b \tag{7}$$

$$x_{j+1} = \psi_j^{\uparrow}(x_j) = MF_j(x_j) \tag{8}$$

$$y_{j+1} = \omega_j^{\uparrow}(y_j) = x_j - MF_j(x_j) \tag{9}$$

Define multi-resolution morphological filter $MF_j(f)$ as :

$$MF_j(f) = \frac{1}{2}(f \circ B_j \bullet B_j + f \bullet B_j \circ B_j) \tag{10}$$

and B_j was a linear SE with length equals to j+1. X_j was the approximate signal, i.e., the ECG signal after de-noising. More improvement in noise suppression performance may be achieved by LMMD method. Consider lifting scheme constructing new detail and signal component at level j as:

$$y'_j = y_j - \pi(xj) \tag{11}$$

$$X'_j = y_j - \lambda(y'_j) \tag{12}$$

where, $\pi: V_j \rightarrow W_j$ was the predicting operator and $\lambda: W_j \rightarrow V_j$ was the updating operator. Reconstructions at level j and j-1 were defined as:

$$\hat{x}_j = x'_j + \lambda(y'_j) \tag{13}$$

$$\hat{x}_{j-1} = \psi^{\downarrow}(\hat{x}_j) + \omega^{\downarrow}(y'_j + \pi(\hat{x}_j)) \tag{14}$$

Block effect was the main cause of waveform distortion in morphological filter based ECG pre-processing method. To address this issue, a novel updating and predicting operator based on cubic spline interpolation was proposed as:

$$\pi(x)(n) = x(n)-x(n+1) \tag{15}$$

$$\lambda(y)(n) = \text{spline}(x(n-1)), x(n+1) \tag{16}$$

where, the predicting operator was the difference between adjacent samples; and updating operator was the interpretation according to the forward and backward sample. Because of the smoothing characteristic of cubic spline interpolation, LMMD algorithm could reduce the block effect and improve the waveform distortion.

RESULTS

LMMD algorithm was applied to a standard testing ECG signal which mixes "clean" ECG signal generated by a bedside monitor and simulated baseline wandering and high-frequency noise, as described in the following subsection. Then the performance of the algorithm as well as comparison with other pre-processing methods was presented in this section.

Standard testing ECG signal: Creating a standard testing ECG signal for simulation provided a common platform to evaluate the performance of pre-processing methods. A "clean" ECG signal generated by a bedside monitor was mixed with simulated baseline wandering and high-frequency noise, given by:

$$S(n) = I(n)+N(n)+B(n) \tag{17}$$

where, S(n) was the combining signal; I(n) was the clean ECG signal generated by a bedside monitor with sampling rate equals to 250 Hz; N(n) was high frequency noise consisting of two parts, probability distribution function is defined as:

$$N(n) = (1-\varepsilon)G_1\left(\frac{n}{\sigma_1}\right) + \varepsilon G_2\left(\frac{n}{\sigma_2}\right) \tag{18}$$

where, G_1 and G_2 denoted probability distribution function of Gaussian random variables and represent background noise and high-frequency noise respectively. Typical setting was $\varepsilon = 0.2$, $\sigma = 0.01$, $\sigma_2 = 0.1$. B(n) was baseline wandering given by:

$$B(n) = B + mn + A\cos\left(2\pi\frac{n}{N} + \varphi\right) \tag{19}$$

let m = 0.0001, B = -0.2, N = 5000, $\varphi = 0$. The standard testing ECG signal generated by above was shown in Fig. 1.

Performance evaluation criterions for pre-processing methods: Three performance evaluation criterions had been chosen as well as considering computing complexity. Let s(i) be the input signal, ŝ(i) be the signal after filtering. N was the number of samples and R was peak-to-peak value of the input signal. The three criterions were given by:

- Mean absolute difference (MAD):

$$MAD = \frac{1}{RN}\|s(i) - \hat{s}(i)\|_1 = \frac{1}{R}\frac{1}{N}\sum_{i=1}^{N}|s(i) - \hat{s}(i)| \tag{20}$$

- Maximum difference (MaxD):

$$MaxD = \frac{1}{R}\|s(i) - \hat{s}(i)\|_\infty = \frac{1}{R}\max_{i=1,\cdots,N}|s(i) - \hat{s}(i)| \tag{21}$$

- Root mean square error (RMSE):

$$RMSE = \frac{1}{R\sqrt{N}}\|s(i) - \hat{s}(i)\|_2 = \frac{1}{R}\sqrt{\frac{\sum_{i=1}^{N}|s(i) - \hat{s}(i)|^2}{N}} \tag{22}$$

The values of these parameters were smaller, the pre-processing performances of algorithms were better.

Baseline correction: An algorithm based on wavelet transformation was considered as a comparison. Firstly, the ECG signal was decomposed by db6 wavelet to the 8th level and a_8 signal component was set to 0 to remove

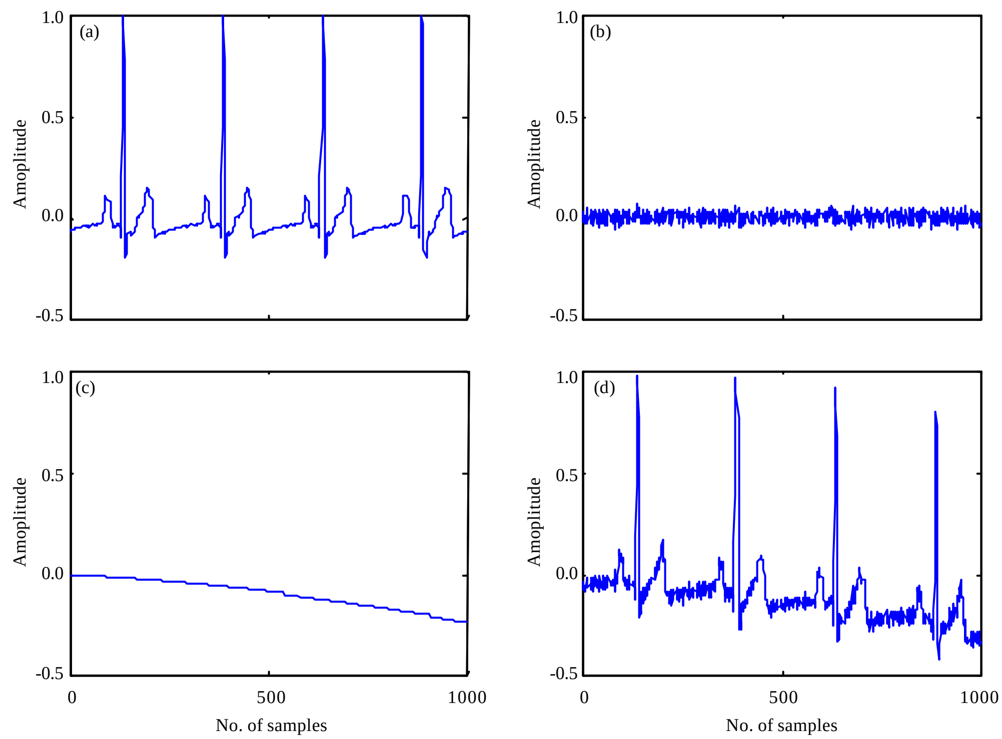

Fig. 1(a-d): A standard testing ECG signal generated by mixing a clean signal with noise and baseline wandering, (a) A clean ECG signal generated by a bedside monitor, (b) Simulated noise, (c) Simulated baseline wandering and (d) The standard testing ECG signal

Table 1: Performance evaluation of baseline correction by db6 wavelet transformation and morphological operation

	db6 wavelet transformation	Morphological operations
MAD	0.0197	0.0518
MaxD	1.04×10^{-4}	1.04×10^{-4}
RMSE	0.0299	0.0543

the baseline component. The simulation results of baseline correction by wavelet transformation and morphological operations were shown in Fig. 2, 3 and Table 1. Figure 2a was baseline component removed by db6 wavelet transformation method. It contained very low frequency component of the ECG signal and could not filter baseline clearly in samples near 1000. As a result, waveform distortions of filtered samples which should be strictly kept in small range for ECG signals, were distinguished, as was shown in Fig. 2b. Figure 3a was baseline component removed by method based on morphological operations. Although the block effect brought by linear SE was obvious, the waveform distortions were visually acceptable in Fig. 3b. Table 1 also demonstrated that wavelet transformation method had superiority in MAD and RMSE and method based on morphological operations could not achieve good performance in RMSE for block effect.

Noise suppression: One comparative algorithm was method based on db6 wavelet transformation. Based on ECG signals after baseline correction and the db6 wavelet transforming results of the original signal, noise suppression was dealt with detail signals on level 1, 2 and 3. De-noised wavelet coefficients were given by:

$$\hat{w}_{j,k} = \begin{cases} \mathrm{sgn}(w_{j,k})(|w_{j,k}| - \lambda) & |w_{j,k}| \geq \lambda \\ 0 & \text{otherwise} \end{cases} \tag{23}$$

where, $\lambda = \sigma\sqrt{2\ln N}$, σ was mean square error of the noise and N was the length of signals. Simulation results were as shown in Fig. 4. There were waveform distortions in QRS complex.

Another comparative algorithm was method based on MMD. Firstly, the signal was decomposed to level 3, as was shown in Fig. 5. Detail signals on level 1 and 2 mainly consisted of noise while detail signal on level 3 mainly included information of ECG signal. Therefore, the ECG signal was decomposed to level 2 to achieve best noise suppression performance.

Simulation by LMMD algorithm was shown in Fig. 6. Approximate signal on level 2 was chosen as the result of

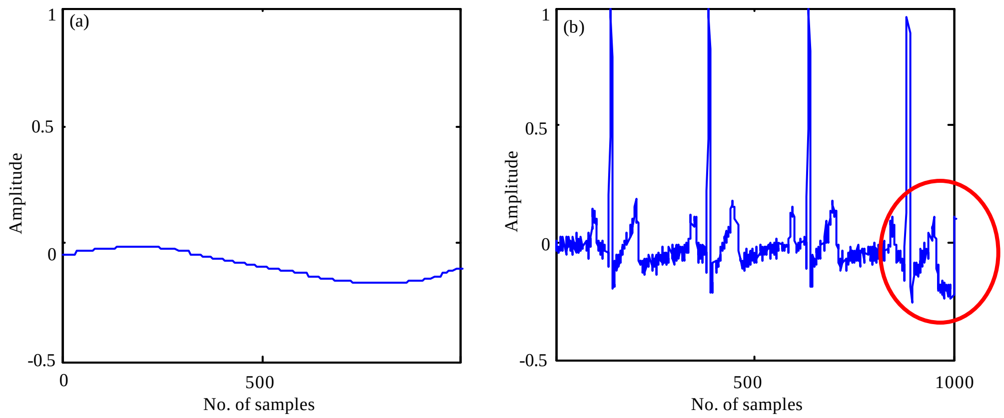

Fig. 2(a-b): Baseline correction by db6 wavelet transformation, (a) Baseline component and (b) ECG signal after baseline correction

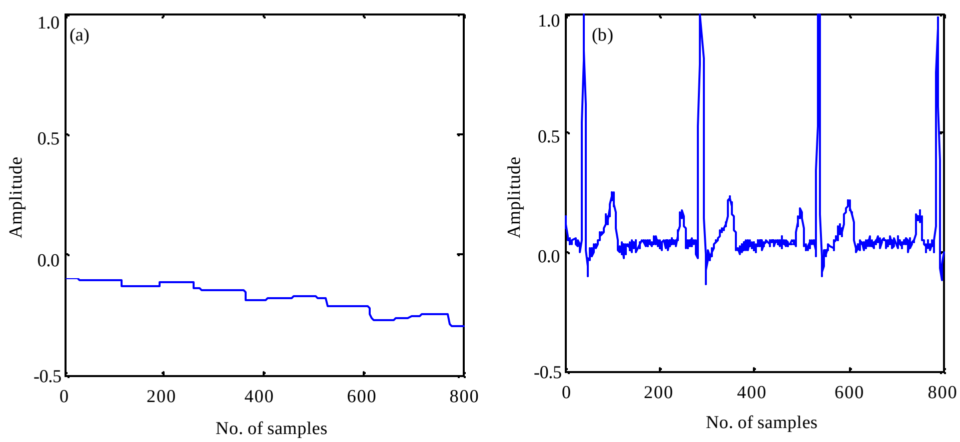

Fig. 3(a-b): Baseline correction by morphological operations, (a) Baseline component, (b) ECG signal after baseline correction

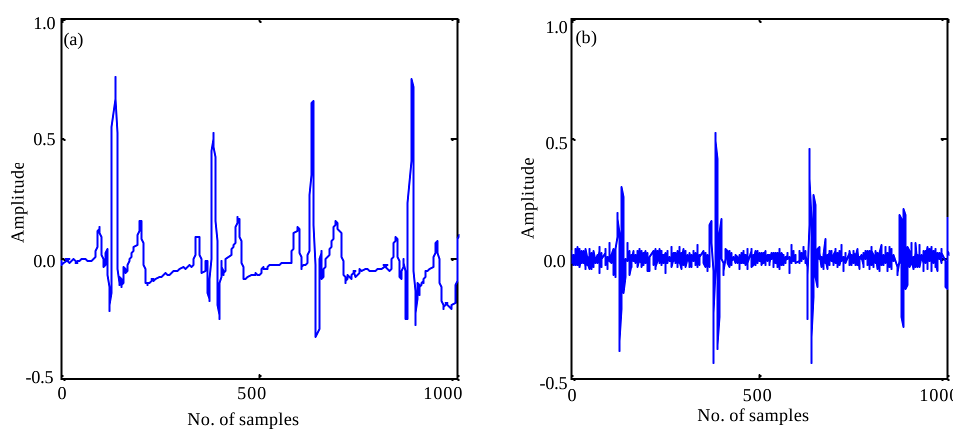

Fig. 4(a-b): Noise suppression by db6 wavelet transformation method, (a) ECG signals after pre-procession and (b) Noise suppressed from the signal

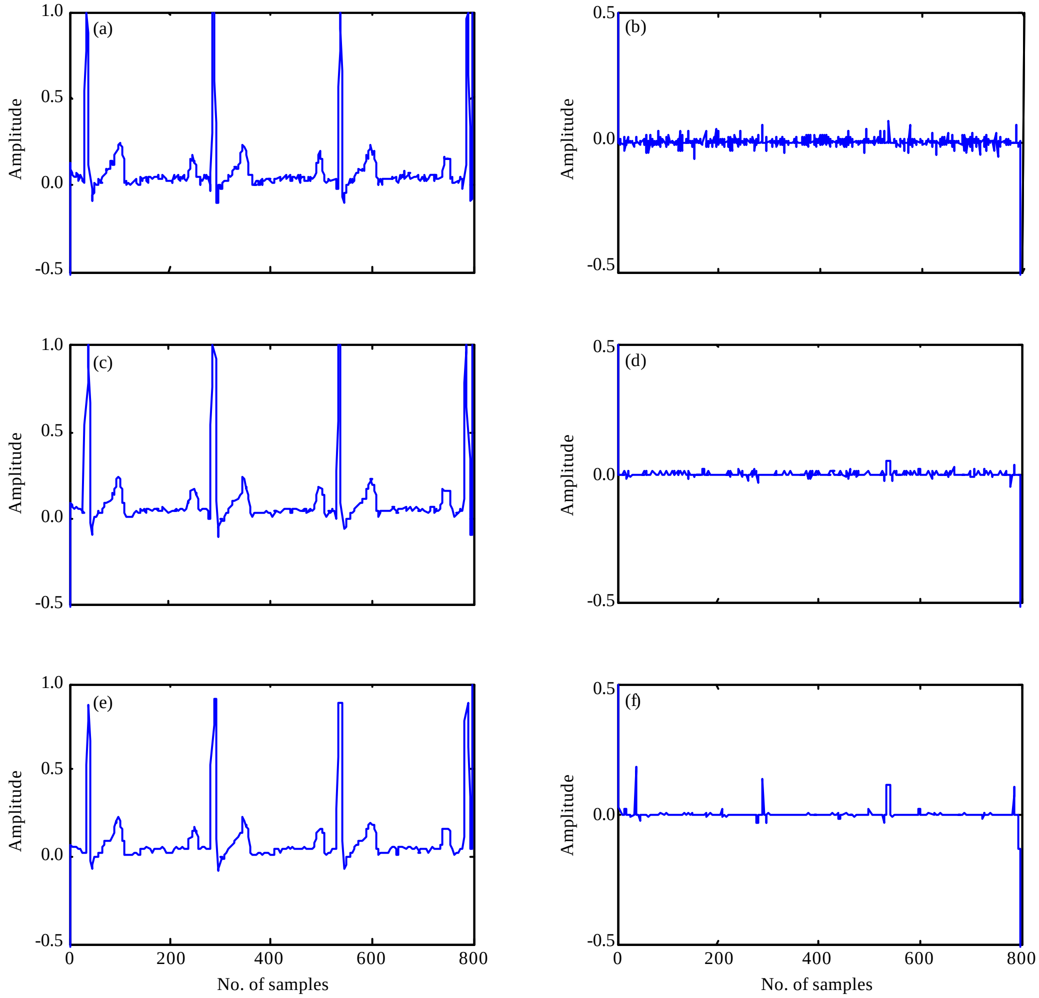

Fig. 5(a-f): Decomposition of ECG signal by MMD method when (a) Approximate signal is on level 1, (b) Detail signal is on level 1, (c) Approximate signal is on level 2, (d) Detail signal is on level 2, (e) Approximate signal is on level 3 and (f) Detail signal is on level 3

Table 2: Performance evaluation of noise suppression by three baseline correction methods

		Morphological operations	
Baseline correction method	db6 wavelet transformation	MMD algorithm	LMMD algorithm
MAD	0.0362	0.0531	0.0527
MaxD	4.11×10^{-4}	1.39×10^{-4}	1.29×10^{-4}
RMSE	0.0659	0.0567	0.0562
Computing time (sec)	1.166	0.189	0.509

noise suppression for the same reason in simulation by MMD method. The performance evaluations of the three noise suppression methods were shown in Table 2. Block effect was improved than that of simulation by MMD method which could be noticed in Fig. 6 and verified by the improvement of MAD, MaxD and RMSE values described in Table 2. Exception of MAD and computing time, LMMD algorithm achieved better performance than the other two methods. For MAD value, LMMD algorithm and MMD algorithm were based on baseline correction by morphological operation which had worse performance than baseline correction by db6 wavelet transformation. By using lifting scheme, the computing time was increased, but still much less than methods by db6 wavelet transformation.

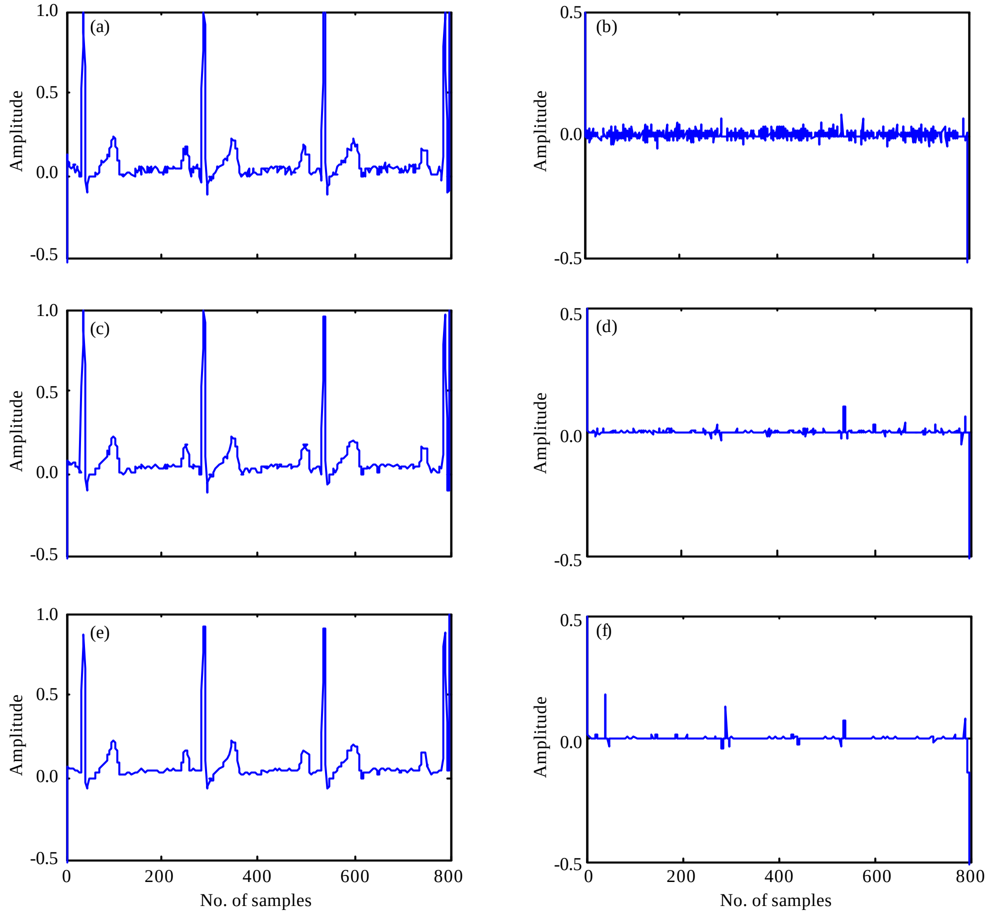

Fig. 6(a-f): Decomposition of ECG signal by LMMD method when (a) Approximate signal is on level 1, (b) Detail signal is on level 1, (c) Approximate signal is on level 2, (d) Detail signal is on level 2, (e) Approximate signal is on level 3 and (f) Detail signal is on level 3

DISCUSSION

ECG signal pre-precession could be divided into two steps: baseline correction and noise suppression. Baseline correction based on high-pass filter was easy to realize by hardware, but useful clinic information in ECG signal was apt to be filtered at the same time. Adaptive filters also had been developed to address this issue, yet they were inflexible to deal with diverse ECG morphology. Baseline correction based on wavelet transformation could smoothly remove baseline component. However, to clearly separate baseline component, the ECG signal should be analyzed to relatively high level. It greatly aggravated the computing burden of the pre-processing system. Furthermore, waveform distortions could not be avoided. Baseline correction methods based on morphological operations such as opening and closing were very popular in recent years. Opening and Closing operations on ECG signals with same length SE (Chu and Delp, 1989) would cause residual pit left by opening operation.

In this study, method based on morphological operations with different length SEs was adopted for baseline correction. Although it caused extra block effect, comparing to methods mentioned above, it could remove the drift properly without serious waveform distortion. And the computation cost was very small.

Noise suppression based on digital filters could remove noise with small computation cost. However, high frequency information in ECG signal, such as R peaks, was usually mixed with noise and waveform distortion could not be avoided. Wavelet transformation method also could not separate noise and information clearly and QRS complexes were apt to be partially filtered. Noise suppression based on morphological operations with triangle SE or SE pair was early method in this field, yet the noise suppression performance was not satisfying (Sun *et al*., 2002). Method based on multi-resolution morphological decomposition could filter noise clearer than method based on wavelet transformation for its shape reorganization specification. Furthermore, the clinical information was reserved better for the smaller waveform distortion. However, it could not avoid block effect brought by linear SE. Lifting scheme constructing MMD made the filtering process converge faster than method based on MMD. And predicting and updating operators were optional depending on the characteristics of the processing signal. The operators based on maximum or median value could not improve block effect and noise suppression performance efficiently. Therefore, in this study, operators based on cubic spline interpolation were proposed to eliminating block effect.

Based on simulation results in this study, the noise suppression performance of LMMD algorithm had better performance on noise suppression than method based on db6 wavelet transformation and multi-resolution morphological decomposition although the weakness in baseline correction by morphological operations. On the other hand, by adopting lifting scheme based on cubic spline interpolation, block effect caused by linear SE was improved which was visually distinguishable and reflected in values of performance evaluation criterions. Furthermore, the waveform distortion in LMMD algorithm was smaller than the other two algorithms which was both acknowledged visually and numerically. The computing time increased by lifting scheme was acceptable when comparing with method based on db6 wavelet transformation.

CONCLUSION

This study presented a novel ECG signal pre-processing method based on lifting scheme constructing multi-resolution morphological decomposition. By adopting cubic spline interpolation based lifting scheme, this method could achieve good performances in noise suppression and reducing block effect with proper computing cost.

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